

ASSIMILATION OF LIDAR OBSERVATIONS IN AEROSOL TRANSPORT MODELS

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ABSTRACT

The use of lidar data in assimilation of aerosol transport models is discussed from the lidar observation point of view. Examples of assimilation of data from the ground-based lidar network (AD-Net) and the space-borne lidar CALIPSO are introduced, and the optimum observations and data processing methods are discussed. A four-dimensional variational data assimilation system for a regional dust model was developed by Yumimoto et al. and applied to analysis of several Asian dust events using the AD-Net dust extinction coefficient data. It was demonstrated that the data assimilation method was useful not only for better reproducing the dust distribution but also for better estimating the dust emission in the source regions. A data assimilation system for a global aerosol model using a four-dimensional ensemble Kalman filter was developed by Sekiyama et al. and applied to CALIPSO data. It was also applied to AD-Net data. The attenuated backscatter coefficient and the volume depolarization ratio were used in the CALIPSO data assimilation successfully. In the assimilation of the ground-based lidars, however, the use of the dust extinction coefficient derived from the backscattering signals and the depolarization ratio was better, because it was difficult with the model to reproduce aerosol distributions in the lower altitudes.

1. INTRODUCTION

Data assimilation is commonly used in meteorological modeling for weather forecasting and reanalysis, however, application of data assimilation methods to chemical transport model is relatively new. The first assimilation of mineral dust data with ground-based lidars was reported by Yumimoto et al. [1], and assimilation of CALIPSO data was reported by Sekiyama et al. [2]. It was demonstrated that the results of data assimilation reproduced Asian dust distribution much better than the models without data assimilation. It was also shown that data assimilation was useful for estimating dust emission more accurately. It was also shown that data assimilation method could be used for accurate forecasting of dust phenomena.

We may also say that data assimilation methods can extract information from observation data effectively. Data assimilation, however, is dependent on the model, and the observations required for data assimilation depends on the purpose and the performance of the models. In aerosol data assimilation, it is essential how

aerosol components and their microphysical and optical characteristics are treated in the model.

2. ASIAN DUST STUDIES WITH 4D-VAR ASSIMILATION OF AD-NET DATA

A four-dimensional variational (4D-Var) data assimilation system for AD-Net was developed by Yumimoto et al. and performed assimilation experiments for several Asian dust events [1, 3-5]. The data assimilation system is based on the real-time regional scale chemical transport model named RAMS/CFORS [6]. The model has 40km horizontal resolution and 40 vertical grid layers. Meteorological boundary conditions to RAMS are taken from NCEP/NCAR reanalysis data with 2.5deg resolution and a 6h interval. RAMS/CFORS has 12 size bins to characterize the dust-particle size distribution, and it considers dust removal processes due to wet deposition, dry deposition and gravitational settling. The optical characteristics of dust are calculated for each size bin and summed to derive the optical parameters such as the extinction coefficient. Consequently, both the mass concentration and the optical parameters should be properly described for transported dust. The dust size distribution at emission was adjusted so that the observed size distribution in dust events in Beijing was reproduced.

In the dust data assimilation, a scaling factor (or the dust emission factor) was introduced in the dust emission function as the control parameter to optimize daily dust emission at each grid. The scaling factor can represent changes in surface conditions such as vegetation growth that are not considered in the original model. The size distribution at dust emission was not changed in the data assimilation. In 4D-Var data assimilation, the adjoint model that propagates the discrepancy between simulated and measured values backward is used to optimize the control parameters.

The dust extinction coefficient profiles at 532nm derived from the two-wavelength (1064nm, 532nm) polarization sensitive (532nm) backscattering lidars in AD-Net were used for the data assimilation. The dust extinction coefficient was derived with the following procedure. Firstly, clouds were detected, and the upper boundary for the aerosol retrieval was determined. The aerosol extinction coefficient was then derived with the Fernald's method with a constant lidar ratio ($S_1=50$). The contribution of mineral dust in the extinction

coefficient was estimated with the method using the depolarization ratio [7, 8]. It is based on the assumption of external mixing of non-spherical dust and spherical aerosols. An error analysis showed that both the error caused by uncertainty in S_1 and the error in estimating dust mixing ratio converge in dense dust condition [9]. One-hour averaged dust extinction coefficient profiles up to 6-km height were used with a 3-hour interval in the data assimilation.

The model region and locations of the AD-Net lidar observation sites are shown in Figure 1.

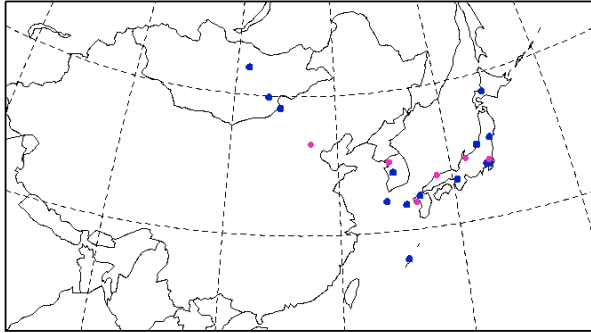


Figure 1. Model region and lidar sites. Data from the stations indicated in red were used in Yumimoto et al. [3].

Figure 2 shows example of time-height indications of dust extinction coefficient at three locations derived from the lidars, calculated with the model without assimilation and with assimilation.

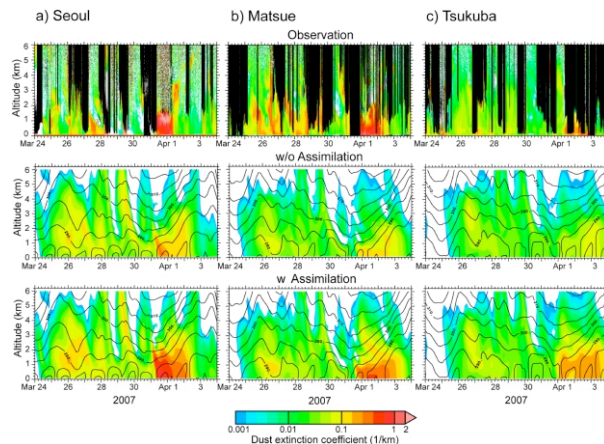


Figure 2. Time-height indications of dust extinction coefficient at Seoul, Matsue, and Tsukuba. The first row shows observation. Second and third rows show modeled dust extinction coefficient without and with data assimilation [3].

As can be seen in Fig. 2, the dust event is better reproduced with the data assimilation. The improvement is natural because the data at these locations were used in the data assimilation. However, the two-dimensional distribution of dust optical depth was also much improved, and it agreed better with

satellite data (OMI AI and MODIS AOT). The assimilated dust extinction coefficient also agreed well with the CALIPSO/CALIOP dust extinction coefficient derived with the same data analysis method in a wide area in downstream. Also, the result of data assimilation reproduced surface PM10 in Korea and Japan very well [8, 10].

In the dust event in the end of March of 2007 shown in Figure 2, the dust emission was underestimated in the original model, and the dust emission increased with the data assimilation. However, in the event in the end of May in 2007, the original model overestimated the dust emission, and the emission was reduced with the data assimilation. It was found that the decrease in dust emission was consistent with the observed vegetation growth in Mongolia during March to May [11].

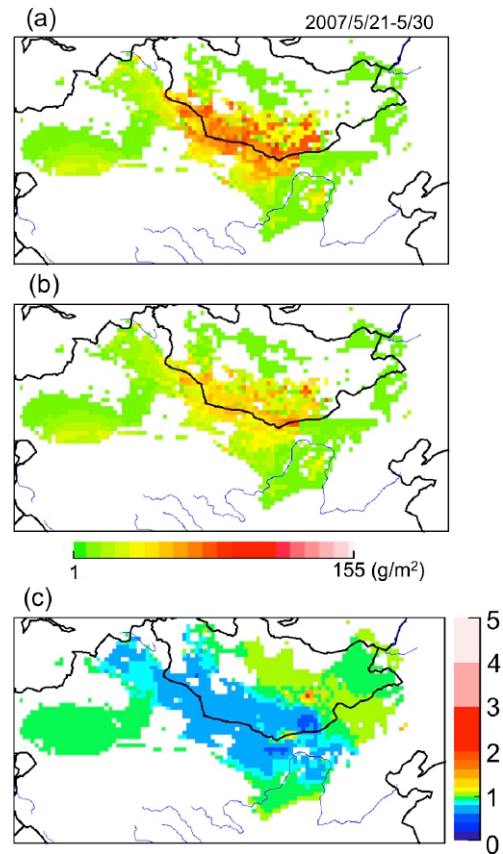


Figure 3. Dust emission for May 21-30, 2007 estimated by CFORS (a) without data assimilation, (b) with data assimilation. (c) Averaged dust emission factor [11]. In this event, dust emission in Gobi desert was suppressed probably with vegetation growth that was not considered in the original model.

The same method as described above for mineral dust can be applied, in principle, to regional air pollution. In that case, the control parameter would be a factor modifying the emission inventory data, but the area of emission is much wider than in dust phenomena, and

the change in emission that is relevant to emission inventory would be extremely slow. We have consequently taken rather a climatological approach than data assimilation, so far, in regional air pollution study [12].

The adjoint model used in 4D-Var data assimilation is a powerful tool, itself, in case studies of air pollution episodes and dust events. Figure 4 shows example of the adjoint variables integrated backward from the observed lidar extinction coefficients for an air-pollution episode (a-c) and for a dust event (d-f). Unlike trajectory analysis, all processes in original model such as diffusion and deposition are included in the analysis with the adjoint model. It can be seen in the air-pollution episode shown in Figure 4 a-c that the aerosol plume was transported from the industrial area in the south of Beijing.

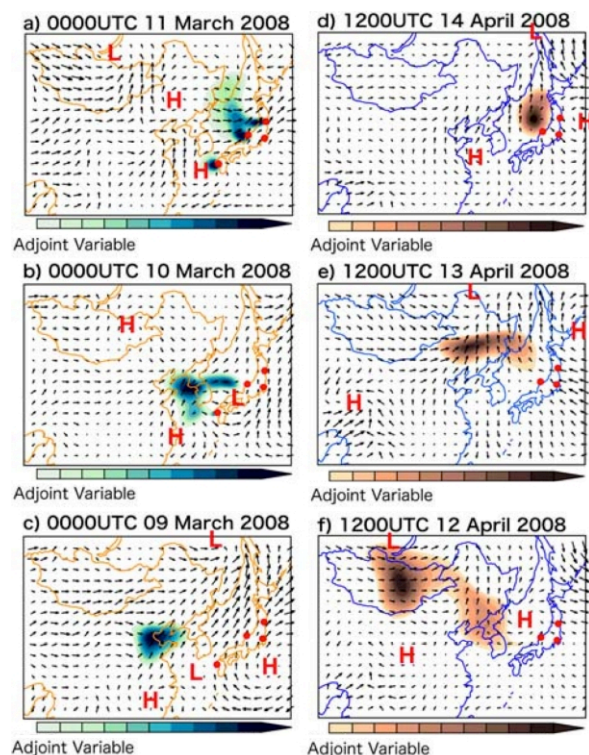


Figure 4. Adjoint variables integrated backward from the observed lidar spherical aerosol extinction coefficient (a-c) and non-spherical extinction coefficient (d-f) [13]. The lidar sites used in the calculation are indicated with the red dots.

3. DATA ASSIMILATION WITH A FOUR-DIMENSIONAL ENSEMBLE KALMAN FILTER

Sekiyama et al. develop data assimilation system for a global aerosol model using a four-dimensional ensemble Kalman filter and performed assimilation of CALIPSO/CALIOP data. Their global aerosol model MASINGAR considered optical properties of

molecules, spherical aerosol (sulfate, sea salt (10 size bins), organic aerosols, and black carbon) and dust aerosol (10 size bins). They used the attenuated backscattering coefficient and the volume depolarization ratio (Level 1B data) for the data assimilation [2, 14]. The control variables were dust concentration, the sulfate concentration, and surface dust emission flux scaling factor. Sekiyama et al. estimated the dust emission factor for the dust events in 2007, and the results were consistent with the results of Yumimoto et al. with RC4 using the AD-Net data [3-5, 11].

Sekiyama et al. also applied the data assimilation system to AD-Net data. In the assimilation of the ground-based lidars, they found it difficult to use the attenuated backscattering coefficient, because the model was not able to reproduce aerosols from local emission sources in the lower layers and to calculate the attenuated backscattering coefficient accurately from the ground. Using the dust and spherical aerosol extinction coefficients, they obtained reasonable results [15]. In the data assimilation using EnKF, the observations close to the emission source was more important than in 4D-Var. It is related to the shorter assimilation window (48 hours in Sekiyama et al.) compared with that in the 4D-Var system (~6 days in [3]).

For dust forecasting, both 4D-Var and EnKF methods can be used, but for data assimilation with very complicated chemical transport models, EnKF method has an advantage because it does not need the adjoint model [15].

4. DISCUSSION

In the data assimilation of AD-Net data introduced above, the dust extinction coefficient derived with the simple one-wavelength method [8] was used. The data analysis method to derive extinction coefficients of dust, sulfate, and sea salt based on a spheroid dust model [16] can also be applied to the AD-Net data. The extinction coefficient estimates for aerosol components derived with such methods can be used for data assimilation.

For (multi-wavelength) high-spectral-resolution lidars (HSRL) (or Raman lidars, if the temporal resolution and the measurement frequency are sufficiently high), it would be better to use the extinction coefficients, the backscattering coefficients, and the particle depolarization ratios, directly, if the aerosol model used in the chemical transport model for data assimilation is sufficiently sophisticated.

One of the targets of the future studies with data assimilation would be constructing aerosol reanalysis data. It would be extremely useful for studies of the

effects of aerosols on the environment and human health.

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